On the Sensitivity of Principal Components Analysis Applied in Wound Rotor Induction Machines Faults Detection and Localization

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Abstract

This paper deals with faults detection and localization of wound rotor induction machines based on principal components analysis method. Both, the localization and the detection approaches consist in analyzing detection index which is established on the latest principal components. Once the faults are detected, the affected state variables are localized by the variables reconstruction approach. The exponentially weighted moving average filter is applied to improve the faults detection quality by reducing the rate of false alarms. An accurate analytical modeling of the electrical machines is proposed and implemented on the Matlab software to obtain the state variables data of both healthy and faulted machines. Several simulation results are presented and analyzed.

Keywords

Principal Components Analysis; Wound Rotor Induction Machines; Faults Detection and Localization; Detection Index; Reconstruction Approach; EWMA filter

Introduction

The necessity for having reliable electric machines is more important than ever and the trend continues to increase. Now, advances in engineering and materials science allow building lighter machines while having a considerable lifetime.

Although researches and improvements have been carried out, these machines still remain the most potential failures of the stator and the rotor. The faults can be resulted by normal wear, poor design, poor assembly (misalignment), improper use or combination of these different causes. Indeed, for many years, faults detection in electrical machines has been the subject of reflection and research projects in various industrial and academic laboratories.

Several diagnosis and control methods exist and already used for the electrical machines monitoring. In this paper, Wound Rotor Induction Machines (WRIM) faults detection and localization based on Principal Components Analysis (PCA) is proposed. PCA is a statistical method used for data or state variables measurement of systems in operation to monitor their behavior.

The PCA principle consists in reducing the size of the representation space of the system [1]. In fault detection approach based on PCA, two methods are proposed [2, 3], Hotelling's T^2 statistical method and Squared Prediction Error (SPE) indicator. The T^2 statistical is calculated with the "l" first principal components while the SPE indicator achieves detection with the residual space. However the two methods have limitations in faults detection [3, 4]. In case of sensors detection, the T^2 indicator is not very efficient because the variations due to the failure may be masked by normal variations of the variables in the first principal components space. And when the considered systems are no longer linear, residues having high variance contain the modeling errors generated by the PCA. Thus the residue having a low variance will have less influence on the SPE quantity with respect to the residues having a higher variance, so that they correspond to the linear redundancy relations or quasi-linear. This sensitivity of the SPE indicator to the modeling errors can create many false alarms. F. Harkat, G. Mourot, and J. Ragot [2] proposed a new method for faults detection and localization based on the sums of squares of the last principal components.

For our case, the method proposed by [2, 4] will be used for the WRIM faults detection and localization.

To improve the faults detection and to reduce the false alarms, the Exponentially Weighted Moving Average (EWMA) filter is used.

The first part of this article deals with the reconstruction principle of the PCA model followed by the WRIM modeling. The second part is focused on the faults detection method by the detection index (D_i). The third part is focused on variables reconstruction combined with the fault indicator D_i for fault location aim. The last part is reserved to the applications of the PCA approach on the WRIM. Several simulations result built with Matlab software are presented and analyzed to show the PCA method sensitivity.

Pca Method Implementation

PCA methods

The PCA method is based on a transformation of space representation of simulation data. The new space is smaller than that of the original space. This method is classified as without model methods [5] and can be seen as a full-fledged system identification method [6, 7]. Each variable to be monitored for the state of the WRIM are expressed by different units and scales. For that, it is preferable to apply a PCA on a centered and reduced measures matrix X (columns of zero means and units standard deviations) [8]. The orthogonal space defined by PCA is generated by the eigenvalues and eigenvectors of the matrix correlation R of X. These values are sorted in descending order in a diagonal matrix. The eigenvalues analysis of the correlation matrix R provides information on the number of principal components to be retained "l" for the PCA model reconstruction [1].

The orthonormal projection matrix P formed by the m eigenvectors associated with eigenvalues of the correlation matrix R is expressed as:

$$P = [p_1, p_2, ..., p_m] \tag{1}$$

The diagonal matrix Λ of the correlation matrix R generated by the eigenvectors associated with eigenvalues λ sorted in descending order is done by:

$$\Lambda = diag(\lambda_1, \lambda_2, ..., \lambda_m) \tag{2}$$

With $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_m$

The orthogonal matrix which represents the projection of X in the PCA new space is T. Mathematically, the PCA decomposes X as follows:

$$T = XP \tag{3}$$

$T \in \Re^{N*m}$ and N is the number of carried out measures of variables to be monitored.

Determination of the structure of the model

To obtain the model structure, the components number "l" to be retained must be determined. This step is very important for PCA construction. Component number can be determined by using:

$$\left(\frac{\sum_{i=1}^{l} \lambda_i}{\sum_{k=1}^{m} \lambda_k} \right) * 100 \geq thc \tag{4}$$

With l<m

Where t_{hc} is an user defined threshold expressed as percentage. Now, user should retain only the components number "l" which was associated in the first term of (4). By reordering the eigenvalues, the minimum numbers of components are retained while still reaching the minimum variance threshold, [9, 10]. The vector of principal components is noted by:

$$T = [t_1, t_2, ..., t_m] \tag{5}$$

Since the aim of PCA is to reduce the space dimension, the "l" first principal components ($l << m$) are the most significant and sufficient to explain the variability of a process. Therefore, the expression of centered and reduced matrix X can be written as follows:

$$X = X_p + E \tag{6}$$

The matrix X_p is the estimated principal part and the matrix E the residual part of X which represents information looses due to the X matrix dimension reduction. They are expressed as follow:

$$X_p = \sum_{i=1}^{l} P_i T_l^{'} \tag{7}$$

$$E = \sum_{i=l+1}^{m} P_i T_l^{'} \tag{8}$$

$T^{'}$ is the transpose of the orthogonal matrix.

Wrim Analytical Modeling

Fig.1 shows the equivalent electrical circuit of the WRIM. Each coil, for both stator and rotor, is modelised with a resistance and an inductance connected in series configuration (Fig. 2).

V_j, I_j and Φ_j (j : A, B, C for the stator phases and a, b, c, for the rotor phases) are respectively the voltages, the electrical currents and the magnetic flux of the stator and the rotor phases, θ is the angular position of the rotor relative to the stator.

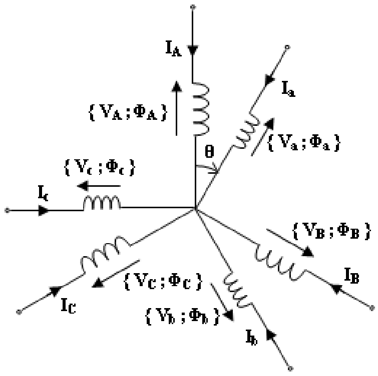

FIG. 1 EQUIVALENT ELECTRICAL CIRCUIT OF THE WRIM

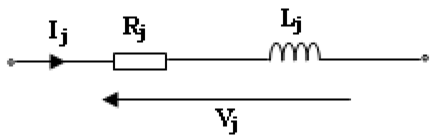

FIG. 2 EQUIVALENT ELECTRICAL CIRCUIT OF THE WRIM COILS

R_j and L_j are the resistances and the own inductances of the stator and the rotor phases. We note the voltages vector ($[V_S]$, $[V_R]$), the currents vector ($[I_S]$, $[I_R]$) and the flux vector ($[\Phi_S]$, $[\Phi_R]$) of respectively the stator and the rotor:

$$[V_S]=\begin{bmatrix}V_A\\V_B\\V_C\end{bmatrix};\ [I_S]=\begin{bmatrix}I_A\\I_B\\I_C\end{bmatrix};\ [\phi_S]=\begin{bmatrix}\phi_A\\\phi_B\\\phi_C\end{bmatrix}$$

$$[V_R]=\begin{bmatrix}V_a\\V_b\\V_c\end{bmatrix};\ [I_R]=\begin{bmatrix}I_a\\I_b\\I_c\end{bmatrix};\ [\phi_R]=\begin{bmatrix}\phi_a\\\phi_b\\\phi_c\end{bmatrix}$$

Taking into account the above assumptions, both stator and rotor three phase voltages and currents are connected to the total magnetic flux by differential equations systems [11]. The stator and rotor voltages vectors expressions are given by:

$$[V_S]=[R_S]\ [I_S]+\frac{d[\phi_S]}{dt} \tag{9}$$

$$[V_R]=[R_R]\ [I_R]+\frac{d[\phi_R]}{dt} \tag{10}$$

$$[\phi_S]=[L_S]\ [I_S]+[M_{SR}]\ [I_R] \tag{11}$$

$$[\phi_R]=[L_R]\ [I_R]+[M_{RS}]\ [I_S] \tag{12}$$

$[R_S]$ and $[R_R]$ are the resistances matrix, $[L_S]$ and $[L_R]$ the own inductances matrix, and $[M_{SR}]$ and $[M_{RS}]$ the mutual inductances matrix between the stator and the rotor coils.

Equations (9) and (10) become:

$$[V_S]=[R_S]\ [I_S]+\frac{d\{[L_S][I_S]\}}{dt}+\frac{d\{[M_{SR}][I_R]\}}{dt} \tag{13}$$

$$[V_R]=[R_R]\ [I_R]+\frac{d\{[L_R][I_R]\}}{dt}+\frac{d\{[M_{RS}][I_S]\}}{dt} \tag{14}$$

By applying the fundamental principle of dynamics to the rotor, the mechanical motion equation is [12]:

$$J_t\frac{d\Omega}{dt}+f_v\Omega=C_{em}-C_r \tag{15}$$

$$\Omega=\frac{d\theta}{dt} \tag{16}$$

$$C_{em}=\frac{1}{2}[I]^t*\frac{d(\ [L]\ )}{d\theta}*[I] \tag{17}$$

J_t is the total inertia brought to the rotor shaft, Ω the shaft rotational speed, $[I]=[I_A\ \ I_B\ \ I_C\ \ I_a\ \ I_b\ \ I_c]'$ the current vector, f_v the viscous friction torque, C_{em} the electromagnetic torque, C_r the load torque applied to the machine, θ the angular position of the rotor with respect to the stator, and $[L]$ the inductance matrix of the machine.

Introducing the cyclic inductances of the stator and the rotor $L_{SC}=\frac{3}{2}L_S$ and $L_{RC}=\frac{3}{2}L_R$ (L_S is the own inductance of the each phase of the stator and L_R is the own inductance of the each phase of the rotor), the mutual inductances between the stator and the rotor coils M_{SR} and pole pair number p, the inductance matrix of the WRIM car be written as follow:

$$[L]=\begin{bmatrix}L_{SC}&0&0&M_{SR}f_1&M_{SR}f_2&M_{SR}f_3\\0&L_{SC}&0&M_{SR}f_3&M_{SR}f_1&M_{SR}f_2\\0&0&L_{SC}&M_{SR}f_2&M_{SR}f_3&M_{SR}f_1\\M_{SR}f_1&M_{SR}f_3&M_{SR}f_2&L_{RC}&0&0\\M_{SR}f_2&M_{SR}f_1&M_{SR}f_3&0&L_{RC}&0\\M_{SR}f_3&M_{SR}f_2&M_{SR}f_1&0&0&L_{RC}\end{bmatrix} \tag{18}$$

With

$$f_1=\cos(p\theta) \tag{19}$$

$$f_2=\cos(p\theta+\frac{2\pi}{3}) \tag{20}$$

$$f_3 = \cos(p\theta - \frac{2\pi}{3}) \qquad (21)$$

Differential equations system modelling

In choosing the stator and rotor currents, the shaft rotational speed and the angular position of the rotor relative to the stator as state variables, the differential equations a system modeling the WRIM is given by:

$$[\dot{X}] = [A]^{-1}([U] - [B][X]) \qquad (22)$$

With

$$[X] = [I_A \ I_B \ I_C \ I_a \ I_b \ I_c \ \Omega \ \theta]^t; \ [A] = \begin{bmatrix} [L] & 0 & 0 \\ 0 & J_t & 0 \\ 0 & 0 & 1 \end{bmatrix};$$

$$[U] = \begin{bmatrix} [V] \\ -C_r \\ 0 \end{bmatrix}; \ [V] = [V_A \ V_B \ V_C \ V_a \ V_b \ V_c]^t;$$

$$[B] = \begin{bmatrix} [R] + \Omega\frac{d[L]}{d\theta} & 0 & 0 \\ -\frac{1}{2}[I]^t\frac{d[L]}{d\theta} & f_v & 0 \\ 0 & -1 & 0 \end{bmatrix}$$

This model of the WRIM will be used to simulate both healthy and faulted operation case of the stator and the rotor. The considered faults are resistances values increases of the stator or rotor windings due to a rise of their temperatures. The following table presents the different parameters of the WRIM:

TABLE I WRIM PARAMETERS

Symbol	Parameter	Value	Units
Lsp	Stator principal inductance	0.397	H
Lrp	Rotor principal inductance	0.397	H
Lsl	Stator leakage inductance	9.594	mH
Lrl	Rotor leakage inductance	9.594	mH
Msr	Stator-rotor mutual inductance	0,3953	H
p	Number of pole pairs	1	-
Jt	Moment of inertia	0.024	$Kg.m^2$
Rs	Stator resistance	2.86	Ω
Rr	Rotor resistance	2.756	Ω
fv	Viscous friction coefficient	1,444	mNm/rad/s

The model has been implemented on Matlab in source codes and allows us to obtain several matrix data for the PCA applications on WRIM faults detection and localization. The WRIM is considered faulted from *t=2s* and coupled to a mechanical load at time *2s*. Nine state variables (*m=9*) have been chosen to be monitored and *10000* measures (*N=10000*) during *4s* are considered.

Fig.3 represents the temporal variations of some state variables (Stator current, rotor current, shaft rotational speed, angular position and electromagnetic torque) showing the steady and transient states of faulted WRIM. Fig.4 shows the zoom of the same state variables variations but only the part during which the machine is in loaded.

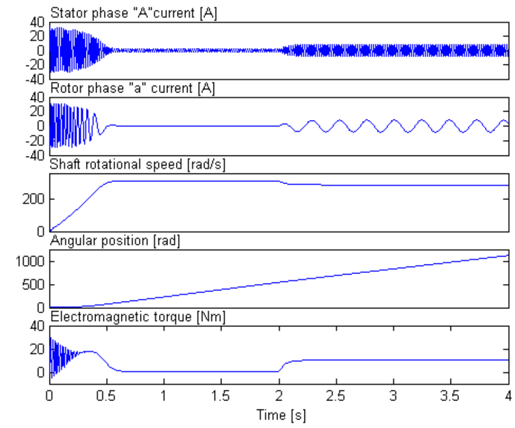

FIG. 3 STATE VARIABLES VARIATIONS VERSUS TIME OF THE FAULTED WRIM LOADED (STEADY AND TRANSIENT STATES)

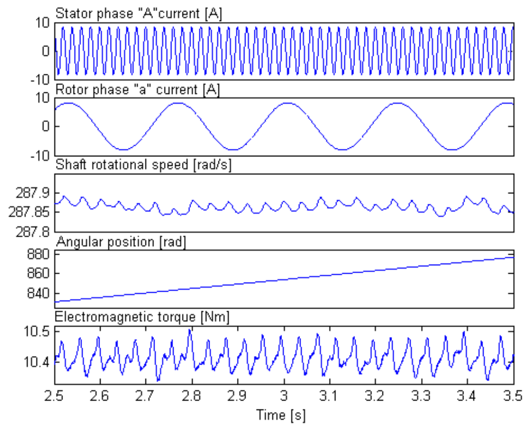

FIG. 4 STATE VARIABLES VARIATIONS VERSUS TIME OF THE FAULTED WRIM (STEADY STATE)

Considered faults

The considered faults are on the resistance values which increase due to a rise of their temperature. In normal operation, a resistance value variation

compared to its nominal value (in ambient temperature, 25°C) is faulted machine due to machine overload or coils fault [10, 13]. The resistance versus the temperature is expressed as:

$$R = R_0(1 + \alpha \Delta T) \tag{23}$$

R_0 is the resistance value at T_0 = $25°C$, α the temperature coefficient of the resistance and ΔT the temperature variation.

Faults Detection Approach

Residues generation

For any measures vector $x(k)$ the equation (6) becomes:

$$x(k) = x_p(k) + e(k) \tag{24}$$

$x_p(k)$ and $e(k)$ vectors represent respectively the estimations vector and the estimation errors vector.

The principal components vector $t(k)$ corresponds to $x(k)$ is expressed as:

$$t(k) = P^{'} x(k) \tag{25}$$

$$t(k) = [t_p(k)\ t_e(k)] \tag{26}$$

$t_p \in \Re^{N*l}$ and $t_e \in \Re^{N*(m-l)}$ are respectively the " l " first principal components vector and the " m-l " last principal components vector.

With this expression (26), there is an similarity on the residue vector $e(k)$ and the final components vector $t_e(k)$.

Detection index "Di" calculation

The fault detection index is based on successive sums of squares of the last principal components [2, 4] and is defined as follows:

$$D_i(k) = \sum_{j=m-i+1}^{m} t_{ej}^2(k) \tag{27}$$

i = 1, 2,…, $(m$-$l)$

At time k, systems are malfunctioning sensing if D_i is greater than a threshold index noted $\tau_{i,\alpha}^2$. α is the false detection probability according to the Khi-2 law with "m" degree of freedom [14]. One can note a strong similarity between the detection index SPE and the detection index D_i. Indeed, D_i corresponds to the SPE indicator calculated by PCA model with $(m$-$l)$ principal components. Thus, this threshold detection can be calculated with an argument similar to that exposed in [4, 14].

The process is considered in default at time k if:

$$D_i(k) > \tau_{i,\alpha}^2 \tag{28}$$

EWMA filter

To reduce false alarm and to improve the faults detection quality, the EWMA filter is applied at time k, and then the "j^{nth}" filtered vector of the last principal components can be written as follow [3, 6 and 15]:

$$t_{efj}(k) = (1-\gamma)t_{ej}(k-1) + \gamma\ t_{ej}(k) \tag{29}$$

γ is the forgetting factor ($0< \gamma <1$) in taking as initial condition $t_{ej}(0) = 0$ and can be calculated by [6, 16]:

$$\gamma = 1 - \exp(-1/\Delta_t) \tag{30}$$

Δ_t is the time step.

Finally, the detection index is expressed as:

$$D_{i\,f}(k) = \sum_{j=m-i+1}^{m} t_{efj}^2(k) \tag{31}$$

And the filtered detection threshold of faults is given by [3, 10]:

$$\tau_{if,\alpha}^2 = \frac{\gamma}{2-\gamma}\tau_{i,\alpha}^2 \tag{32}$$

It should be noted that many research works uses the threshold detection for sensor faults, but our case concerns faults detection of systems.

Faults Localisation Approach

When a fault is detected, it is necessary to localize or identify the involved variables. There are several methods for faults localization:

- residues structuring approach,
- partial PCA approach,
- Calculation of variables contributions to the detection indicator approaches.

But [45] showed the disadvantage of the methods mentioned above. Then, in this paper, faults location of WRIM state variables is based on the variables

reconstruction combined with the filtered detection index.

The localization of the WRIM affected state variables by the combined approach is based on two methods combination:

- variables reconstruction by PCA,
- detection index

The method consists in eliminating the fault influence on D_i when the affected variable is reconstructed.

To localize faults on the indicator, faults directions projected in the residual space should not be collinear [8]. After the j variable number reconstruction, fault indicator in noted D_i^j.

One can also use the EWMA filter to reduce the localization false alarms and to improve the localization indicator quality. If D_{if}^j is the filtered detection index of the j variable number, the localization indicator can be obtained by:

$$L_{if}^j = \frac{D_{if}^j}{\tau_{if,\alpha}^2} \tag{33}$$

The variable for which the localization indicator L_{if}^j is less than one is the offending variable. This method can be used for the multiple faults localization in reconstructing the supposed faulted variables simultaneously.

Simulation Results and Discussion

To validate the proposed models and the efficiency of the chosen approaches, the established models have been implemented in Matlab. Nine WRIM state variables (stator three phase currents, rotor three phase currents, shaft rotational speed, angular position and electromagnetic torque) have been considered. The matrixes data of the healthy and faulted WRIM obtained by the analytical model of the machine are introduced in PCA model to show faults detection and localization performances.

For the electrical machines diagnosis, many methods are used to detect the presence or absence of faults, occurred at t=2s, and to locate the time when it began to appear on the machine windings. Two types of faults levels are considered in the system (10%, 30%). These values correspond to the rise of the stator or rotor coils resistance. We can mention the temporal representation (Fig. 5, Fig. 6 and Fig. 7) and the signal frequency analysis. Although they have demonstrated their efficiency, the state variables representations between them also show their advantages. They can be performed without mathematical transformation (Fig. 7).

Also, the electromagnetic torque variations versus the shaft rotational speed clearly show the WRIM operation zone in the presence of faults (Fig. 7). After several simulations, we suggest some of these methods to highlight the place of PCA among them. In the Fig.5 and Fig.6, the figures clearly show that it is difficult to visualize changes in signals and the fault appearance time.

However, by analyzing the residues of the stator current by PCA (Fig.8, Fig.9), the fault appearance time is located on the two signals. The case of a healthy machine that has a zero residue is almost coincident with the x-axis. These observations are found in the case of the rotor current (Fig. 8). In Fig.5 and Fig.6, the presences of faults with the conventional temporal representation are no more evident than that using PCA method (Fig. 8 and Fig. 9). This one shows the residue analysis interest on PCA method. Fig.6 and Fig.9 expose the real and residue variations of the electromagnetic torque versus time. With Fig.6, the fault appearance time is not easy to locate. However, with PCA method, the variation of residues in the electromagnetic torque with and without faults can be easily detected. The real (Fig. 6) and residue (Fig. 9) variations of the electromagnetic torque versus shaft rotational speed of the machine show again that it is much more interesting to treat the state variables of the machine with PCA method to detect the presence or absence of faults on the windings. The difference between healthy and faulted operation (Fig. 9) are clearer. It is almost not found in the real variation representations (Fig. 6). Fig.8 to Fig.11 highlight the major potential benefits of state variables treatment by PCA method which easily shows faults detection and locate time of fault appearance.

With PCA method application, all representation (Fig. 10 and Fig. 11) well shows the differences between healthy and faulted WRIM. In the healthy case, residues are zero. When faults appear, the residue representations have an effective value with an absolute value greater than zero. In the Fig.10 and Fig.11, the healthy case is represented by a right line placed on the x-axis. Also, in taking into account "1" last principal component, Fig.10 shows peak variations

at t=2s (measure number 5000), time at which the faults are introduced. The peaks are attenuated immediately after but the signals are shifted.

With "2" last principal components, the detection is improved because after the first peaks, other peaks (in the presence of faults) are greater than those in the case of the healthy machine.

In the case of the faults detection, Fig.12 and Fig.13 show the variations of the filtered and the no filtered detection index of both "1" and "2" last principal components versus the measure number of the faulted WRIM. The threshold detection is represented on both figures. In the part where the machine is coupled to a mechanical load, the shapes exceed repeatedly the threshold index. This overrun corresponds to the presence of faults. The last principal components numbers do not have large influences on the curves shape for both filtered and no filtered detection index.

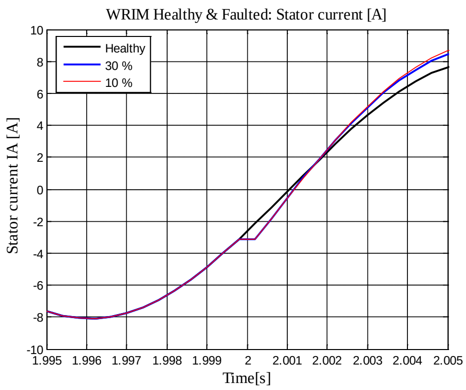

FIG.5 REAL VARIATIONS VERSUS TIME OF THE STATOR CURRENT OF THE HEALTHY AND FAULTED WRIM

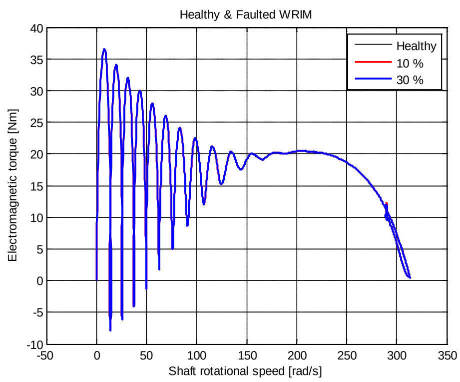

FIG.6 REAL VARIATIONS OF ELECTROMAGNETIC TORQUE VERSUS THE SHAFT ROTATIONAL SPEED OF THE WRIM

However, in the case of the no filtered shape, excessive values appear. These values show a bad detection of the no filtered data compared to those of the filtered data. This behaviour can be corresponding to alarm false for some cases. Data filtering is therefore important in faults detection process to avoid alarm false.

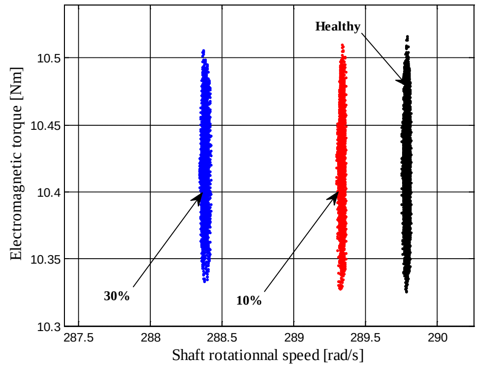

FIG. 7 REAL VARIATIONS OF ELECTROMAGNETIC TORQUE VERSUS THE SHAFT ROTATIONAL SPEED OF THE WRIM

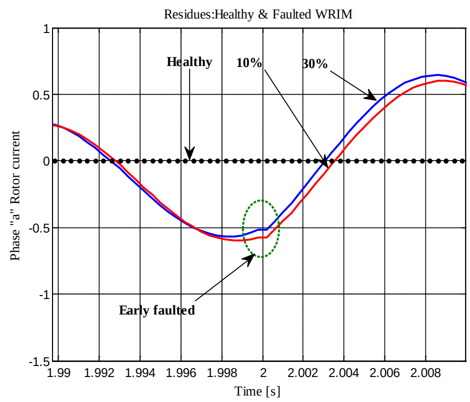

FIG.8 EARLY FAULTED IN VARIATIONS OF THE ROTOR CURRENT RESIDUES VERSUS OF THE HEALTHY AND FAULTED WRIM

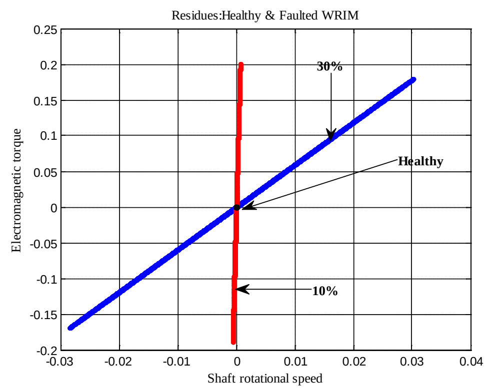

FIG. 9 VARIATIONS OF ELECTROMAGNETIC TORQUE RESIDUES VERSUS THE SHAFT ROTATIONAL SPEED RESIDUES OF THE WRIM

Fig.14 and Fig.15 represent respectively the no filtered and the filtered localization index versus the WRIM state variables. The threshold of the localization index is represented on both figures. All variables having a localization index founding below the threshold variation are the affected variables.

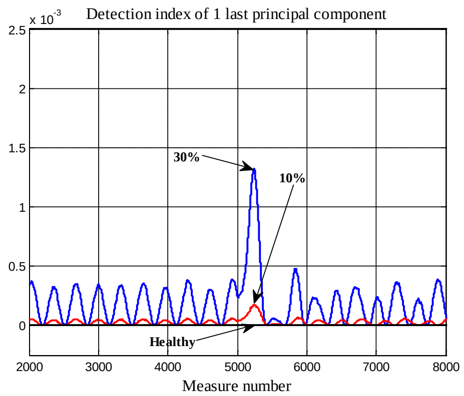

FIG. 10 DETECTION INDEX OF “1” LAST PRINCIPAL COMPONENT VARIATIONS VERSUS THE MEASURE NUMBER OF THE WRIM

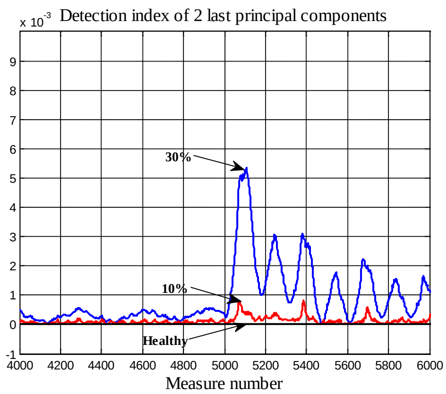

FIG. 11 DETECTION INDEX OF “2” LAST PRINCIPAL COMPONENTS VARIATIONS VERSUS THE MEASURE NUMBER OF THE WRIM

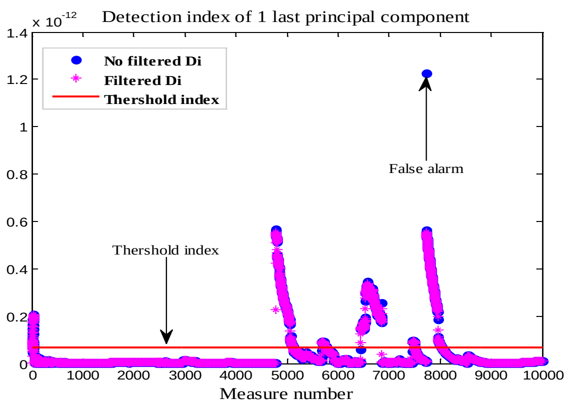

FIG. 12 FILTERED AND NO FILTERED DETECTION INDEX OF “1” LAST PRINCIPAL COMPONENT VARIATIONS VERSUS MEASURE NUMBER OF FAULTED WRIM

In the case of the no filtered localization index, only variable “4”and “6”correponding to the phase “*a*” and phase “*c*” rotor currents are not affected. In the filtered localization index case, stator phase “*a*” and phase “*b*” are not affected by faults. This last better reflects the WRIM behaviour in the case of the considered fault type. As in the case of the fault detection approach, the use of filter is necessary for faults localization.

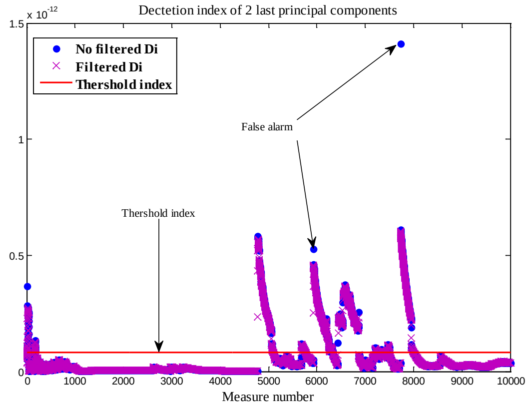

FIG. 13 FILTERED AND NO FILTERED DETECTION INDEX OF “2” LAST PRINCIPAL COMPONENT VARIATIONS VERSUS MEASURE NUMBER OF FAULTED WRIM

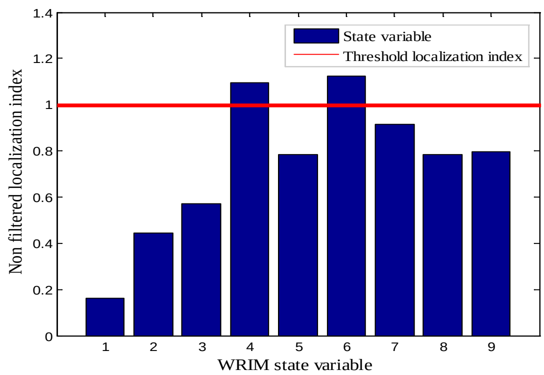

FIG. 14 NO FILTERED LOCALIZATION INDEX VARIATION VERSUS THE STATE VARIABLES

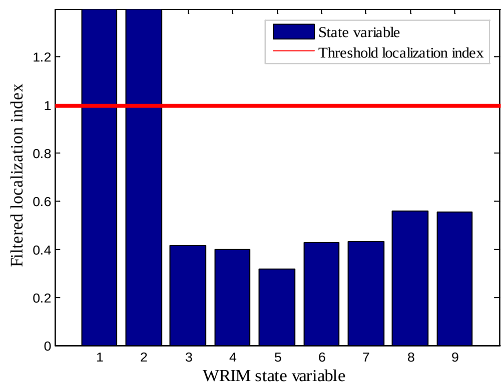

FIG. 15 FILTERED LOCALIZATION INDEX VARIATION VERSUS THE STATE VARIABLES

Conclusion

PCA method based on residues analysis has been established and applied on WRIM diagnosis. In the case of temporal variation and without PCA, the electromagnetic torque and the shaft rotational speed are the more affected by the considered fault type. An accurate analytical model of the machine has been proposed and simulated to perform the healthy and

faulted data for PCA approach need.

WRIM faults detection and localization approaches based on PCA method are proposed. For that, an accurate analytical modeling of the WRIM has been carried out. The established models are implemented in Matlab. Nine state variables of the machine have been considered. Simulation results show the efficiency of the detection and localization based on respectively the detection index and localization index. The use of EWMA filter on both detection and localization has helped to avoid some false alarm. Also, filtered localization index better show the affected variables.

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